An enhanced face recognition technique based on Overlapped Modular PCA approach for cropped Log-polar images

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***Abstract* ---An algorithm for human face recognition, which is based on Overlapped Modular Principal Component Analysis Approach on the Cropped Log-polar images, is presented in this paper. In this technique all the image are divided into sub-images called modules and to avoid loss of features at division lines, overlapped sub-images are taken through the division lines. This method is applied on the Cropped Log-polar images. In this method all the images are converted into log-polar form and from all those transformed images only the facial areas are extracted and they are called as cropped log-polar images. Since some local features do not vary with orientations, poses and illumination variations it is expected that the proposed method is capable to cope up with these variations. Recognition Rates from experimental results show the superiority of the present method over Modular PCA and the conventional PCA methods in tackling face images with different orientations, pose variations and changes in illuminations.**

***Index Terms* --- Face Recognition, PCA, Modular PCA, Overlapped Modular PCA, Cropped Log-polar images.**

I. INTRODUCTION

Works related to Face Recognition techniques have crossed many milestones and tried to overcome many barriers to achieve good recognition rate. Machine recognition of faces is emerging as an active research area spanning several disciplines such as image processing, pattern recognition, computer vision and neural networks. Still there are spaces to work to develop some better methodologies so that comparatively higher Recognition Rate can be attained. Face recognition is a difficult problem due to the general similar shape of faces combined with the numerous variations between images of the same face. Automatic recognition of faces is considered as one of the fundamental problems in computer vision and pattern analysis and many scientists from different areas have addressed to it. Recognition of faces from an uncontrolled environment is a very complex task: lighting condition may vary tremendously; facial expressions also vary from time to time; face may appear at different orientations and a face can be partially occluded. Further, depending on the application, handling facial features over time (aging) [18] may also be required. Chellappa et al. [1] presented different approaches related to face recognition methods e.g. statistical-based, neural-network based and feature-based methods. Face images are expressed as a subset of their eigenvectors with principal component analysis (PCA)[14][15][16][17], and also called eigenfaces [3][4][5][9][11].

The main idea of this work is to improve the recognition rate of face images subject to variations in face orientation, head pose, illumination and so on. As stated earlier, PCA method has been a popular technique in facial image recognition. But the said technique is not highly accurate when the illumination, orientation and pose of the facial images vary considerably. Later on Modular PCA, which was proposed by Gottumukkal and Asari [2], is an extension of the conventional PCA method. The recognition rate is supposed to be increasing with this method and complexity, memory utilization is said to be reduced to a noticeable amount. In this paper an extension of the modular PCA is proposed with the name overlapped modular PCA to increase the number of extracted features from each sub-image which might be ignored or missed while dividing into modules in modular PCA. In the overlapped modular PCA method the face images are divided into smaller images, some more modules are created taking the common pixel situated along the division line and the PCA method is applied on each of them. Whereas in the traditional PCA method the entire face image is considered, hence large variation in pose[19] or illumination[20] will affect the recognition rate profoundly. Since in the case of modular PCA method the original face image is divided into sub-images, the variations in pose, orientation or illumination in the image will affect only some of the sub-images, hence we expect this method to have better recognition rate than the conventional PCA and modular PCA method. To recognize the face images more accurately with lower complexity only the

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pixels of face portion is cropped, neglecting the other unwanted pixels, from the log-polar converted images prior to apply overlapped modular PCA on those cropped images.

This paper is organized as follows: Section 2 explains Modular PCA method. Section 3 illustrates overlapped modular PCA. Section 4 describes the process of cropping log-polar images converted from face images from face databases. Section 5 finally presents the simulation results obtained by applying the PCA method, modular PCA method and the proposed overlapped modular PCA method over both normal images, log-polar images and cropped log-polar images with large orientation, pose and light variations. Lastly, conclusion is drawn in section 6.

II. REVIEW OF MODULAR PCA METHOD

PCA is appropriate when we have obtained measures on a number of observed variables and wish to develop a smaller number of unknown variables that will account for most of the variance in the observed variables. PCA generates a set of orthogonal axes of projections known as the eigenvectors, of the input data distribution in the order of decreasing variances. It is possible that PCA performs better with a smaller gallery, and its performance degrades more rapidly as gallery size increases. The Modular PCA algorithm when compared with conventional PCA algorithm has an improved recognition rate for face images with large variations in lighting direction and facial expression as described in [2]. In the present work, the face images are divided into smaller sub-images and the PCA approach is applied to each of these sub-images. Since some of the local facial features of an individual do not vary even with the change in pose, lighting direction, age and facial expression, we expect the proposed method to be able to cope with these variations. This work is an attempt to measure the accuracy of the conventional PCA method and modular PCA method are evaluated under the conditions of varying expression, illumination and pose using standard face databases.

The PCA based face recognition method is not very effective under the conditions of varying pose and illumination, since it considers the global information of each face image and represents them with a set of weights. Under these conditions the weight vectors will vary considerably from the weight vectors of the images with normal pose and illumination, hence it is difficult to identify them correctly. On the other hand if the face images were divided into smaller regions and the weight vectors are computed for each of these regions, then the weights will be more representative of the local information of the face. When there is a variation in the pose or illumination, only some of the face regions will vary and rest of the regions will remain the same as the face regions of a normal image. Hence weights of the face regions not affected by varying pose and illumination will closely match with the weights of the same individual's face regions under normal conditions. Therefore it is expected that improved recognition rates can be obtained by following the modular PCA approach. We expect that if the face images are divided into very small regions the global information of the face may be lost and the accuracy of this method may deteriorate.

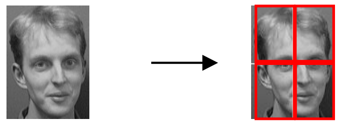

Fig.1. image of an individual from ORL database shows the module generation

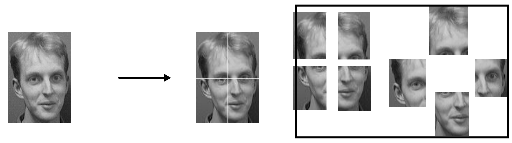

Fig.2. Image segmentation in virtual level for a face image.

III. OVERLAPPED MODULAR PCA METHOD

This approach is an extension of Modular PCA method where in addition to modules of Modular PCA for each boundary of these modules an overlapped module is taken in to consideration. Those extra modules are generated by taking equal number of pixels from both left and right sides of two adjacent modules. The proposed method is expected to give good consistent recognition rate than Modular PCA due to inclusion of subtle details of features, which might have been placed in two different modules otherwise.

The algorithm for overlapped modular PCA is as follows:

Step1: M is the number of training images, N is the number of sub-images (each image in the training set is divided into N smaller images). Each sub-image is represented as:

$$I_{ij}(m,n)=I_i\left(\frac{L}{\sqrt{\frac{N}{2}}}(j-1)+m,\frac{L}{\sqrt{\frac{N}{2}}}(j-1)+n\right)\quad \forall i,j \tag{1}$$

where $1 \le i \le M$, $1 \le j \le N$, $1 \le m,n \le L/\sqrt{N/2}$ (as the size of each sub-image is $L^2/(N/2)$)

Step2: Average image is computed as:

$$A=\frac{1}{M.N}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij} \tag{2}$$

where $1 \le i \le M$, $1 \le j \le N$

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Step3: Normalize each training sub-image as: $Y_{ij} = I i_j - A \quad \forall i, j$ where $1 \le i \le M$, $1 \le j \le N$ (3)

Step4: The covariance matrix is computed as:

$$C = \frac{1}{M . N} \sum_{i=1}^{M} \sum_{j=1}^{N} Y_{ij} . Y_{ij}^{T} \tag{4}$$

where $1 \le i \le M$, $1 \le j \le N$

Step5: Eigenvectors C are computed that are associated with M' largest eigenvalues. (e.g. $E_1, E_2, \ldots, E_{M'}$)

Step6: Image data is reconstructed.

Step7: Weights are computed from the eigenvectors from the training sub-images as well as test sub-images. For training sub-images:

$$W_{pnjK} = E_K^T . (I_{pnj} - A) \quad \forall p, n, j, K \tag{5}$$

K takes the values 1, 2,…,M′, n varies from 1 to Γ, Γ being the number of images per individual, and p varies from 1 to P, P being the number of individuals in the training set. For test sub-images:

$$W_{test\ jK} = E_K^T . (I_{test\ j} - A) \quad \forall j, K \tag{6}$$

Step8: Mean weight set of each class in the training set is computed from the weight sets of the class.

$$size10\, T_{pjK} = \frac{1}{\Gamma} \sum_{K=1}^{M'} \sum_{n=1}^{\Gamma} W_{pnjK} \quad \forall p, j \tag{7}$$

Step9: The minimum distance is computed.

$$D_{pj} = \frac{1}{M'} \sum_{K=1}^{M'} |W_{test\ jK} - T_{pjK}| \quad ;$$

$$D_p = \frac{1}{N} \sum_{j=1}^{N} D_{pj} \tag{8}$$

$\min(D_p) < \theta_i$ for a particular value of p, the corresponding face class in the training set is the closest one to the test image. Hence the test image is recognized as belonging to the p^{th} face class.

IV. CROPPED LOG POLAR METHOD

It is known that the log-polar algorithm bears conventional approach to convert an image data from Cartesian to log-polar format [21]. The proposed method differs in dimensionality reduction at the preprocessing step. From Fig.3 it can be observed that common background pixels are concentrated below the frame of the converted image and taking that advantage the segments in the images bearing the pixels with equal values are deleted. The matching ratio for two images with larger similar background and different objects appeared to be highest and as a result any classifier must show poor performance. This method is expected to give better recognition rate because similar features are deleted keeping discriminating features intact for images belonging to different classes.

V. TEST RESULTS

PCA, modular PCA, and overlapped modular PCA are tested over normal face images as well as Logpolar and cropped Logpolar images varying number of training images, number of sub-images and number of eigen vectors. Consideration of more eigenvectors results in good recognition rate and after a point it becomes constant. However increase in computational cost is linear with the increase in number of eigenvectors.

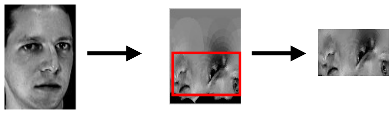

Fig.3. Cropping from a Logpolar image.

The testing is done for ORL face database [22] and UMIST face database [23].

A. Test results Using ORL face database:

The ORL face database is comparatively simple database to handle with. It contains ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying lighting etc. All the images were taken against a dark homogeneous background. With this database maximum recognition rate of 95% has been achieved.

In the Fig.4 a comparative recognition rates among Conventional PCA, PCA with Logpolar, Modular PCA with Logpolar and MPCA varying the number of training images for ORL face database have been shown. It has been noticed that the conventional PCA achieves good result rather than other methods.

In the Fig.5 comparative Recognition Rates among Modular PCA with single module, 4 (four) modules and 16 (sixteen) varying the number of training images have been shown. Modular PCAs with 4- and 16-modules achieved good recognition rates.

In Fig.6 Recognition Rates have been plotted in the graph which have been achieved applying PCA and Modular PCA techniques varying number of eigenvectors. This shows that both the methods provided consistent recognition rate and the rate achieved in the case of PCA is little higher then the MPCA in case of higher eigenvectors.

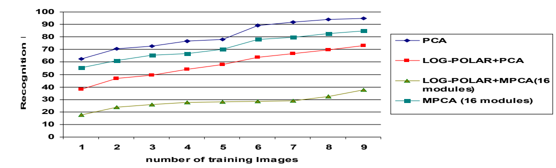

Fig. 4. Recognition rates of PCA, Logpolar+PCA, logpolar+MPCA (16 modules), MPCA (16 modules) varying number of training images

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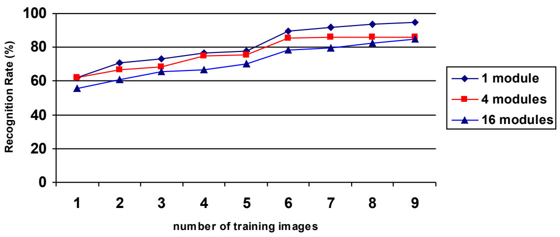

Fig. 5. Recognition Rates of MPCA with respectively 1, 4, 16 modules with varying number of training images.

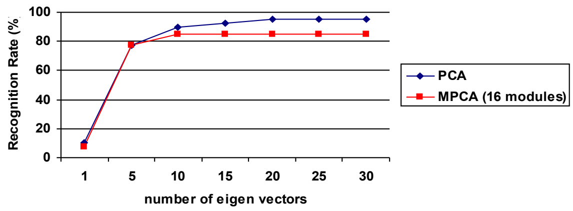

Fig. 6. Recognition Rates of PCA and MPCA with varying number of eigenvectors.

B. Test results for UMIST face database

The UMIST face database is comparatively a complex database then ORL to handle with. It has been discussed that, there are total 564 different images of each of 20 distinct subjects. For all the subjects various pose angles are provided. Each and every image of all the subjects is taken on random facial orientation i.e. without following any specific uniform orientations for all the subjects. Along with this database maximum of 95% of recognition rate has been achieved in this project. The outputs achieved in form of recognition rate are graphically represented below in a comparative manner varying different parameters as well as working methodologies and algorithms as mentioned throughout the project.

Experimental results, shown in Fig.7, reveals that with the higher number of training images recognition rates for PCA, MPCA, Overlapped MPCA are similar.

In Fig.8 Recognition Rates obtained for Logpolar with each of PCA, MPCA and Overlapped MPCA are compared with varying number of training images. It has been found that in this case higher recognition rate is achieved in case of MPCA with Logpolar than the other methods.

Fig. 7. Recognition rates of PCA, MPCA (4 Modules), Overlapped MPCA (8 modules) varying number of training images

Fig. 8. Recognition rates of PCA, MPCA (4 Modules), Overlapped MPCA (8 modules) with Log-polar method varying number of training images

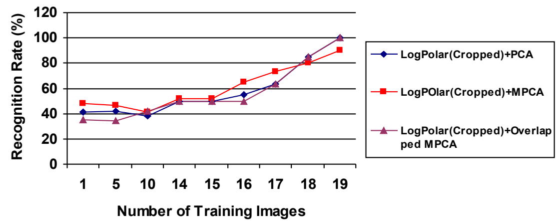

Fig. 9. Recognition rates of PCA, MPCA (4 Modules), Overlapped MPCA (8 modules) with Cropped Log-polar method varying number of training images

Fig.9 provides comparative results obtained for PCA, MPCA and overlapped MPCA, each with cropped Logpolar transformation by varying number of training images. It has been found that overlapped MPCA with cropped Logpolar method provides superior performance than both PCA and non-overlapped MPCA with same Cropped Logpolar images for large number of training images.

VI. CONCLUSIONS

In this work overlapped Modular PCA has been applied to Cropped Log-polar face images and the experimental results of this technique has been compared with conventional PCA and Modular PCA. Cropped log-polar transformation technique can be used as an alternative to existing Log-polar conversion method as it maximizes the discriminating capability of features. Moreover, this technique minimizes the image dimension, which reduces space and time complexity of the Face Recognition algorithm. Also, experimental results suggest that the Overlapped modular PCA can be used in lieu of existing PCA or Modular PCA. In particular, the said method will be useful over cropped log-polar images for identification system subjected to large variations in illumination and expression.

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